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Estimating the Value of an Early-Warning System

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An early-warning system generates economic value to the extent that it improves decision making. The value of the information hinges on the degree to which a timely response, aided by warnings, facilitates successful damage mitigation. USDA's Coordinated Framework for Soybean Rust includes a network of sentinel soybean plots and wild kudzu stands monitored by extension agents for the presence of soybean rust, a potentially recurring threat to the U.S. soybean crop since 2005. The linchpin in this early-warning system is a website that provides near real-time, county-level information on the location of the disease. We consider factors that may influence information value.

Information is valuable when it allows decision makers to adjust their actions to better suit the situation at hand. When information allows many individuals to improve their decision making, a governmental role in its provision may be justifiable, because individuals may be unable to coordinate and finance its collection and dissemination. Of course, just because information can embody the public good attributes of nonrivalry and nonexcludability does not necessarily imply a role for public policy. One must still consider social costs and benefits.

While cost calculation might be relatively straightforward, valuing information can be challenging. In this paper, we consider an illustrative example provided by a recent USDA-led effort to provide real-time information for a new threat to the U.S. soybean crop, *Phakopsora pachyrhizi*, a fungus that causes soybean rust (SBR). SBR, a recurrent problem for soybean producers in much of the southern hemisphere, was first detected in the United States in 2004, late enough in the growing season that it posed no threat to that year's soybean crop. After overwintering in southern states along the Gulf of Mexico, SBR posed a new, uncertain,

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and potentially severe threat to the U.S. soybean crop at the beginning of the 2005 growing season (Skokstad).

The USDA-led framework provides real-time SBR information via a website (http://www.sbrusa.net) that reports findings from sentinel plots where experts regularly monitor for soybean rust. Findings are pooled together with weather forecasts and aerobiological analyses to forecast the likely future spread of the fungus. The overarching purpose of the framework is to provide farmers with sufficient notice so they can make appropriate decisions as to the use of preventive and curative fungicides on their soybean fields.

In the three full years since its first detection in the United States, SBR has posed little threat to the U.S. soybean crop. Given the expense of developing the website and its underlying infrastructure, some have questioned whether the framework was a worthwhile endeavor. After all, if farmers had simply managed their crops as if there were no SBR threat, they may have fared as well or better than they did in the presence of the Coordinated Framework. However, this view overlooks a key point: although weather conditions have not yet facilitated dispersion of SBR spores to key soybean-producing regions, this could not have been known in advance. A potential SBR threat existed at the beginning of the 2005 season, but how farmers might have prepared for that threat in the absence of the USDA framework is not clear. Indeed, without the framework, individual farmers may have incurred even greater expense by monitoring their own fields, perhaps spraying fungicides for a threat that did not exist in their area, or forgoing planting entirely.[1] More generally, this view overlooks the fundamental notion that information value should be assessed from an *ex ante* perspective. Quantifying the *ex ante* value involves determining the expected value of actions with and without the benefit of information and subtracting the latter from the former. This can be challenging because it involves determining decisions that would have been made without the information, and what the consequences of those decisions would have been. Perhaps more elusively, it also hinges on what farmers' expectations would have been without the USDA framework.

We develop estimates of the *ex ante* value of information provided by the USDA framework from the vantage point of the beginning of the 2005 growing season (Roberts et al.). We show how various factors influence the size of this value, including the costs and efficacy of available fungicides, farmers' prior beliefs about the likelihood of infection, the perceived accuracy of the framework's SBR forecasts, and farmers' risk preferences. The value may also depend on how soybean prices would be affected by SBR-induced production shocks. Our analysis builds on standard Bayesian decision theory.

Most empirical value-of-information studies consider only the value of perfect information. In this study, we develop a set of assumptions that allows us to consider the value of information over a continuum of information qualities. This is useful in gauging the value of more realistic information systems. It also facilitates straightforward valuation of marginal improvements in information quality.

We find the value of information depends on many factors, but most importantly farmers' prior beliefs about SBR risk at the beginning of the growing season and the accuracy of the system's forecast. These factors cannot be quantified precisely, so we consider information values over a range of assumptions about prior beliefs, forecast accuracy, and other factors. Even if forecasts are imprecise, resolving only 20% of SBR infection uncertainty for all fields planted with soybeans, the system's value in 2005 was an estimated \$11 million. If forecasts resolved 80% of infection uncertainty, the estimated value was \$395 million. Our analysis suggests that the value of the information in 2005 likely exceeded costs of developing the information, reported to be between \$2.5 and almost \$5 million.

Three additional factors affect estimated information values: anticipated price shocks in the event of a large rust outbreak, soybean farmers' aversion to risk, and heterogeneity of farmers' prior beliefs of an infestation. We find that all of these factors tend to reduce the largest estimated values and increase the smallest estimated values, but the effects are relatively small in magnitude. The potential benefits of the framework suggest that similar programs for other crop pests can be cost effective if, as in the case of soybean rust, preventive action can strongly mitigate damages in the event of an outbreak.

Bayesian Updating with Information Accuracy

In this section, we review Bayesian decision theory (Hirschleifer and Riley; Schimmelpfennig and Norton) and use it to develop a simple model to value information provided by the USDA-led framework about impending SBR infections. We also develop a set of simplifying assumptions to derive a scalar index of information accuracy (Lawrence).

We begin by characterizing the problem in terms of a payoff matrix that maps a finite set of possible farmer actions $x \in \{x_1, x_2, \ldots, x_X\}$ and a finite set of mutually exclusive states $s \in \{s_1, s_2, \ldots, s_S\}$ to an $X \times S$ matrix of possible outcomes, the elements of which are denoted by $p_{x,s}$. The unconditional probability that any given state s will occur is π_s. These probabilities are subjective: they pertain to a farmer's beliefs about the chances that each state will occur, and we assume these beliefs are consistent with the laws of probability (all $\pi_s \geq 0$ and $\Sigma_s \pi_s = 1$).

An information signal is modeled as a random variable M, which might realize outcomes such as m_{L}, signaling "low risk of infestation," or m_{H}, signaling a "high risk of infestation." In general, there may be any number of possible messages. The message is valuable if it arrives before the farmer chooses an action and causes the farmer to change beliefs about the probability that states s will occur. The *posterior* probability, the probability of s given M (ϕ_{sM}), is linked to the prior probability (π_s) using Bayes rule

$$\phi_{s,M} = \Pr[s \mid M] = \pi_s \frac{\Pr[M \mid s]}{\Pr[M]}. \tag{1}$$

The quality of the information signal depends on the magnitude of the difference between ϕ_{sM} and π_s. A perfect information signal would cause a complete resolution of uncertainty, so that if the state s^* ultimately arises, $\phi_{s^*M} = 1$ and $\phi_{-s^*M} = 0$. Thus, for perfect information, the number of possible outcomes from the message M must equal the number of possible states S, and the distribution of M must be identical to the distribution defined by the probabilities π_s. That is, $\Pr[M = s] = \pi_s$ and $\Pr[s = M \mid M] = 1$. For example, if there are two states of the world, "infestation" and "no infestation," then analogous messages that forecast "impending infestation" or "no impending infestation" would occur with the same frequency as infestations themselves ($\Pr[M = s] = \pi_s$), and the messages would always be correct ($\Pr[s = M \mid M] = 1$).

The more realistic and interesting case is when information is imperfect. In general, the number of possible messages may be greater than, less than or equal to the number of possible states, and both the conditional and unconditional probability distributions of messages can take many forms. One way to simplify the issue is to assume the message is a forecast that predicts which state will occur, and that the unconditional probability distribution of messages equals the probability distribution of states. Hence, as in the case of perfect information, $\Pr[M = s] = \pi_s$. We therefore define the unconditional probability density function of M using the same notation as the states, e.g., π_M. Unlike the case of perfect information, however, $\Pr[s = M \mid M] < 1$; that is, it is anticipated that the forecast may be inaccurate. From Bayes rule, we can see that in this special case

$$\phi_{sM} = \Pr[s \mid M] = \Pr[M \mid s] = \frac{\Pr[M \cap s]}{\pi_s}. \tag{2}$$

By simplifying the problem in this way, we can model information quality using a single index of message accuracy $\alpha \in (0, 1)$, where information quality tends to zero as α tends to 0 and information quality tends to perfect accuracy as α tends to 1. We do this by setting

$$\Pr[M \cap s] = \pi_s \pi_M + \alpha(1 - \pi_s \pi_M). \tag{3}$$

This expression implies that M and s are independent when $\alpha = 0$ (the message contains no information) and perfectly correlated ($\Pr[M \cap s] = \pi_s$) when $\alpha = 1$ (perfect information). The expression in (3) is simply a linear interpolation between these two extremes. Under this set of assumptions, the posterior distribution is linked to the prior distribution by

$$\phi_{sM} = \frac{\pi_s \pi_M + \alpha(1 - \pi_s \pi_M)}{\pi_s}. \tag{4}$$

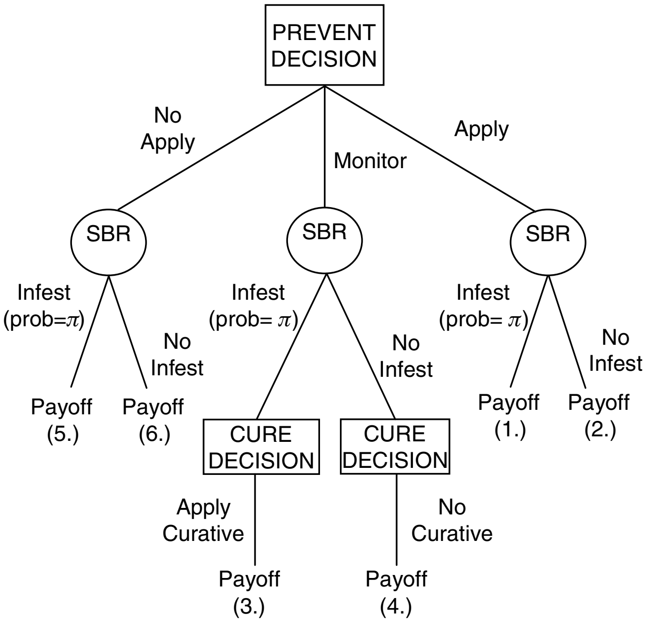
The value of information depends on the effect the message has on the decisions farmers make. Without a message, farmers maximize expected profit given their prior beliefs, π_s. We denote these actions by x^*. With information, farmers choose their actions to maximize expected profits conditional on the message M. We denote these actions by $x^* \mid M$. Payoffs are given by the combination of the state that occurs and action chosen and denoted p_{xs}. Taking expectations, the *ex ante* value of information given by message M is therefore

$$\mathrm{VOI} = \sum_M \sum_s \phi_{sM}\, p_{sx^* \mid M} - \sum_s \pi_s\, p_{sx^*}. \tag{5}$$

Estimating the Value of the SBR Monitoring Framework

To estimate the value of the SBR monitoring framework we must delineate farmers' possible management strategies (actions) and possible payoffs. We assume

Figure 1. Decision tree without information about soybean rust infection



Notes: Square boxes indicate farmers' decisions and the circles represent nature's random decision whether or not to infest. The payoffs (1–6) are described in table 1.

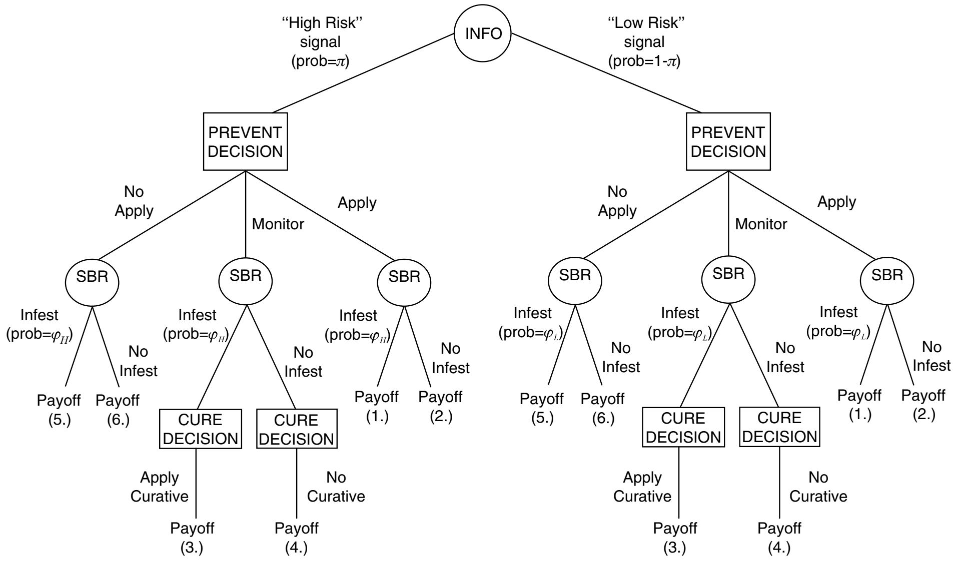
Table 1. Possible outcomes stemming from *P. pachyrhizi* threat

Management Strategy	Infection	No Infection
Apply preventive treatment	1 1% yield loss, cost of \$25.63/acre	2 Cost of \$25.63/acre
Monitor fields and apply curative treatment if SBR	3 7% yield loss, cost of \$20.52/acre	4 Cost of \$6.71/acre
No rust management	5 25% yield loss	6 Base return

Source: Johansson et al.

three management strategies: (*a*) apply a preventive fungicide before soybean rust occurs; (*b*) intensively monitor fields and apply a curative fungicide if soybean rust is detected; or (*c*) do nothing. The payoffs and profit-maximizing strategies depend on the costs of preventive and curative fungicides, monitoring costs, expected yield losses in the event of an infection, soybean prices, and farmers' perceptions of the probability that infection will occur. The decision tree in figure 1 shows how the three strategies, crossed with two possible states (infestation and no infestation), lead to six possible payoffs, which are summarized in table 1.[2] The costs in this table are treatment cost, not the cost of the yield loss.

Figure 2. Decision tree with partial information about soybean rust infection



Notes: Square boxes indicate farmers' decisions and the circles represent nature's random decisions about the information signal and whether or not to infest. The payoffs (1–6) are described in table 1.

Figure 2 illustrates the decision tree for an environment with an imperfect information signal. In this environment, management decisions are made after receiving an information signal, *M*, which changes farmers' beliefs about infection from the prior, π to posterior ϕ_H or ϕ_L, depending on whether it is a "high-" or "low-risk" signal. The accuracy of the signal, α, ranges continuously between 0 and 1: the higher is α, the more the signal changes farmers' beliefs. If information quality were perfect, we would expect only two signals, one perfectly forecasting an impending arrival of SBR and one perfectly forecasting the nonarrival of SBR—that is, ϕ_H would equal 1 and ϕ_L would equal zero. To approximate a continuum of information qualities, we suppose there remain just two signals, but that the signal itself may have different levels of accuracy. If neither of the two signals contained informational content, they would not alter farmers' priors ($\pi = \phi_H = \phi_L$), and farmers would choose the same management strategy in the partial information environment as they would in the no-information environment.

Because we do not have objective estimates for information accuracy, we evaluate farmers' optimal conditional strategies and expected profits over a range of accuracies: $\alpha = 0.2$ (low), $\alpha = 0.5$ (medium), and $\alpha = 0.8$ (high). One may think of these information qualities as the proportion of uncertainty resolved by the partial information. We then calculate farmers' overall expected profits by multiplying conditional expected profits by the probability of each signal and summing them, as per equation (5).

Quantifying Payoffs and Probabilities

Soybean Yield Impacts

Fungicide efficacy trials from Brazil and Paraguay in 2001–2003, aggregate yield data for 10 Brazilian states during 1993–2002, and data on the introduction of *P. pachyrhizi* into those states were used to estimate rust-free yields and treated and untreated yield impacts (Livingston et al.). Rust-free yields averaged 2.604 (±0.422) metric tons per hectare, and treated and untreated yields averaged 2.578 (±0.201) and 2.025 (±0.363) metric tons per hectare. Estimated treated and untreated yields were therefore lower by an average 4.3% (±5.2%) and 25.0% (±11.9%), respectively, than estimated rust-free yields.

We use the untreated yield impacts to estimate payoffs when rust occurs but no fungicide is applied. Because the treated yield impacts were estimated with yield data reported from soybean plots sprayed with curative, preventive, or curative plus preventive fungicides, we must separate impacts of the different kinds of treatments. Replicating the methods in Johansson et al., we find that the average yield impact for the preventive class of fungicides is −0.97%. The average yield impact for the curative class of fungicides is −6.95% with a mean of 1.39 applications evaluated (see table 2 and Livingston et al.).[3]

Prior Infection Probabilities

We develop regional proxies for prior probabilities of SBR infestations using data on wheat stem rust, a disease that spreads through the air much like SBR. Stem rust epidemics of wheat for 1921–62 (Hamilton and Stakman) are used to estimate how often *P. pachyrhizi* spores may be present in most states where soybeans are produced (U.S. Department of Agriculture, 2005). We also use data on daily temperature extremes, rainfall, and humidity for 1992–2001 to estimate the proportion of years in which conditions may favor the development of soybean rust in each state (Livingston et al.). *P. pachyrhizi* may be able to overwinter along the coastlines of Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas (Pivonia and Yang); therefore, we assume that climatic conditions will favor introduction of soybean rust in all years for these states. In addition, because *P. pachyrhizi* is an obligate parasite that can not live without a host plant, we use data on the most likely soybean planting and harvesting dates for each state (U.S. Department of Agriculture, 1997) to estimate how often climatic conditions and host availability may favor rust epidemics.

To estimate state-level prior probabilities for rust infections, we use the product of the proportion of years that stem rust epidemics actually occurred and the proportion of years that climates favored the spread of rust. This assumes climatic conditions affecting the dispersal of spores and those affecting the broader establishment of rust in an area are independent (Hamilton and Stakman). To convert state-level prior probabilities to regional probabilities, we weight states by average 1995–2004 soybean production (U.S. Department of Agriculture, 1998–2005). Over all U.S. soybean acres, these calculations imply an average prior probability of rust infection equal to 0.53. Across regions, the priors are 0.67, 0.55, 0.55, 0.49, 0.62, 0.43, 0.76, and 0.51 for Appalachia, Corn Belt, Delta, Lake States, Northeast, Northern Plains, Southeast, and the Southern Plains, respectively.[4] These

Table 2. Yields with preventive and curative fungicides

Rust-Free Yield Estimate (Tons/Acres)	Efficacy Trial Yield (Tons/Acres)	Preventive Yield Impact (%)	Treatments (Number)	Curative Yield Impact (%)	Treatments (Number)	Source
2.223	1.914			−14	2	a
2.223	1.765			−21	2	
2.223	1.776			−20	2	
2.549	2.149			−16	2	b
2.549	2.190			−14	2	
2.549	2.090			−18	2	
2.549	1.832			−28	2	
2.549	2.767			9	1	c
2.549	2.946			16	1	
2.549	2.548	0%	1			
2.549	2.712	6%	1			
2.549	2.926			15	1	d
3.359	3.969	18%	1			e
3.359	3.641	8%	1			
3.359	3.813	14%	1			
3.359	3.531			5	1	
3.359	3.656			9	1	
3.359	3.313	−1%	1			
3.359	3.375	0%	1			
3.359	2.938	−13%	1			
3.359	2.984	−11%	1			
3.359	2.703			−20	1	
3.359	3.313			−1	1	
3.359	3.250	−3%	1			
3.359	3.328	−1%	1			
3.359	2.984			−11	1	
3.359	3.203			−5	1	
2.750	2.469	−10%	1			f
2.750	2.516	−9%	1			
2.750	2.406	−13%	1			
2.750	2.578			−6	1	
2.750	2.625			−5	1	
2.686	2.568	−0.97%	1.00	−6.95	1.39	Mean

Source: (a) Bayer (2003a) (Trials 1 and 2). Lower bound of rust-free yield estimate for Mato Grasso do Sul 2001–02. (b) Bayer (2003b) (Trial 14). The estimate for rust-free yield in Minas Gerais 2002–03. (c) Bayer (2003b) (Trial 15). The estimate for rust-free yield in Minas Gerais 2002–03. (d) Bayer (2003b) (Trial 16). The estimate for rust-free yield in Minas Gerais 2002–03. (e) BASF (2003) (Jesus, Paraguay). The upper bound of the rust-free yield estimate for Parana 2002–03. (f) BASF (2003) (Pirapo, Paraguay). The estimate for rust-free yield in Mato Grasso do Sul 2002–03.
Note: Blank fields indicate no data: Each study considers either preventive or curative fungicide treatments.

probabilities are used to estimate information values in the base case (table 3) and other scenarios.

Our rather high estimated priors may appear inconsistent with the actual U.S. SBR experience after 2005 since SBR has not yet posed a serious threat to the overall U.S. soybean crop. It is possible, however, that our estimated infestation

Table 3. Base case information values

Region	Prior Belief of Infection (Probability)	No Info Decision (P,M, or N)	Expected Yield Without SBR (Bushels/Acre)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P,M, or N)	High Risk EV (Dollars)	Low Risk Decision (P,M, or N)	Low Risk EV (Dollars)	EV With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Appalachia	0.67	M	35.80	0.2	P	77,530	M	83,015	79,358	714	0.64
	0.67	M	35.80	0.5	P	77,282	M	89,572	81,379	2,734	2.45
	0.67	M	35.80	0.8	P	77,034	N	99,743	84,604	5,959	5.33
Corn Belt	0.55	M	44.60	0.2	P	91,776	M	96,390	93,873	166	0.22
	0.55	M	44.60	0.5	P	91,497	M	100,413	95,549	1,842	2.48
	0.55	M	44.60	0.8	P	91,217	N	106,510	98,169	4,461	6.01
Delta	0.55	M	31.80	0.2	M	93,057	M	103,850	97,963	0	0
	0.55	M	31.80	0.5	P	87,415	N	114,271	99,623	1,659	0.85
	0.55	M	31.80	0.8	P	86,890	N	130,022	106,496	8,533	4.36
Lake States	0.49	M	41.50	0.2	M	56,831	M	60,227	58,573	0	0
	0.49	M	41.50	0.5	P	55,720	M	62,708	59,304	731	1.37
	0.49	M	41.50	0.8	P	55,509	N	67,085	61,446	2,873	5.38
Northeast	0.62	M	38.70	0.2	P	41,276	M	43,889	42,281	172	0.36
	0.62	M	38.70	0.5	P	41,145	M	46,559	43,228	1,119	2.37
	0.62	M	38.70	0.8	P	41,015	N	50,697	44,739	2,630	5.56

Continued

Table 3. Continued

Region	Prior Belief of Infection (Probability)	No Info Decision (P,M, or N)	Expected Yield Without SBR (Bushels/Acre)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P,M, or N)	High Risk EV (Dollars)	Low Risk Decision (P,M, or N)	Low Risk EV (Dollars)	EV With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Northern	0.43	M	36.30	0.2	M	67,717	M	72,916	70,688	0	0
Plains	0.43	M	36.30	0.5	P	63,767	N	77,141	71,409	721	0.82
	0.43	M	36.30	0.8	P	63,428	N	83,496	74,895	4,207	4.78
Southeast	0.76	M	25.20	0.2	M	1,887	M	4,078	2,408	0	0
	0.76	M	25.20	0.5	P	1,765	N	7,146	3,046	638	1.44
	0.76	M	25.20	0.8	P	1,715	N	11,095	3,949	1,540	3.48
Southern	0.51	M	26.00	0.2	M	21,244	N	29,647	25,343	371	0.24
Plains	0.51	M	26.00	0.5	M	15,652	N	39,069	27,075	2,102	1.38
	0.51	M	26.00	0.8	P	13,499	N	48,491	30,568	5,596	3.67
Other	0.53	M	33.90	0.2	M	66,216	M	72,469	69,159	0	0
	0.53	M	33.90	0.5	P	63,194	N	77,837	70,085	926	0.84
	0.53	M	33.90	0.8	P	62,869	N	86,977	74,214	5,056	4.61

Notes: In decision columns (b), (e), and (g), M is monitor/cure, P is prevent, and N is do nothing. In (f), (h), and (j), EV is expected value. Zero values of information are due to rounding of discrete data.

rates continue to be reasonable, even after 2005 when U.S. farmers had not any firsthand experience with SBR. Some support for this view stems from the fact that, even following a benign year in 2005, survey data indicate many farmers remained concerned about possible SBR infection in 2006. For example, while over 50% thought it was "very unlikely" that their fields would be infested, and 22% thought it "somewhat unlikely;" there were still 6% and 3% of farmers who respectively thought infestation was "somewhat" and "very likely" in their fields. Seventeen percent were uncertain whether their fields would be infested or not. This means over a quarter of surveyed soybean farmers thought that infestation was more likely than not, or were uncertain. While we cannot discern precise probabilistic priors from qualitative survey responses, these data do indicate that farmers perceived significant infestation risk in 2006. Thus, it is plausible that beliefs were just somewhat more pessimistic a year earlier in 2005.

In 2006–2008, the actual incidence of SBR steadily increased. Plant pathologists now believe it will take a number of years for *P. pachyrhizi* spores to build up to natural equilibrium levels.[5] Thus, individual-season prior infection beliefs are likely rising again after an initial fall after the 2005 season.

Given the difficulty of determining prior beliefs of infection and the fundamentally subjective nature of those beliefs, we supplement our base-case prior probabilities with a sensitivity analysis that varies prior infection probabilities from 10% to 120% of our base-case estimates. We also look more closely at the soybean-rich Corn Belt, considering for that region a continuum of prior beliefs that ranges from zero to one.

Base Case Results

The value of information is the difference in expected profits between the partial-information environment (figure 2) and the no-information environment (figure 1). Results reported in table 3 indicate that the value of information varies between zero and $6.01 per U.S. soybean acre, depending on information quality and assuming prior infestation beliefs equal our estimated infestation probabilities. In table 4, we report information values for a whole range of priors, scaled as a percent of our estimated priors. A striking result of this sensitivity analysis is the extreme nonlinearity of the information value with respect to the prior infestation probabilities.

To further characterize the nonlinear relationship between information value and prior infestation beliefs, we focus on the Corn Belt region, which has the nation's largest share of soybean production. For this region, we examine the full range of possible priors (figure 3). Values for all three information qualities peak at prior infection probabilities of $\pi = 0.19$ and 0.63. These probabilities mark switching points in farmers' optimal strategies. Below a 19% chance of infection, the best strategy is to do nothing; between a 19% and 63% chance of infection, the best strategy is monitoring and application of curative fungicides if infected; above a 63% chance of infection, the best strategy is to use preventive fungicides. For a given quality of information, values are highest near these switching points, because information has the greatest scope for altering farmers' decisions and reducing the chance of *ex post* errors. Of course, the better the quality of information, the more *ex post* errors are reduced, creating greater value. When information is

Table 4. Sensitivity analysis

Region	Info Quality	Prior (Percentage of Base Case Regional Assumptions) 10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	110%	120%
Appalachia	Low	0	773,791	2,414,674	3,790,561	0	0	0	0	0	2,878,572	3,627,729	1,417,390
	Medium	2,163,377	4,849,248	8,057,614	10,687,488	7,103,426	4,139,743	3,517,786	4,475,203	7,478,491	11,024,865	10,796,467	7,282,721
	High	5,297,414	11,021,060	17,170,939	22,646,064	21,810,990	21,402,149	21,419,540	21,863,163	22,733,019	24,029,107	21,433,568	15,435,828
Corn Belt	Low	3,841,390	13,601,571	29,280,542	12,101,905	0	0	0	0	0	7,733,674	36,062,733	36,087,619
	Medium	23,077,459	49,854,163	80,330,111	75,728,903	49,650,701	33,572,259	27,332,872	43,762,883	63,324,222	86,016,890	111,840,886	107,481,912
	High	53,107,148	108,946,524	167,518,130	190,045,566	186,262,155	185,210,973	186,892,021	191,305,297	198,450,803	208,328,537	220,938,501	202,966,395
Delta	Low	0	0	176,857	736,029	1,545,310	1,714,964	158,625	0	0	0	0	0
	Medium	621,699	1,399,717	2,334,053	3,424,707	4,671,680	5,185,235	3,879,005	2,729,095	1,948,953	2,061,546	2,515,688	3,618,741
	High	1,680,548	3,497,716	5,451,502	7,541,909	9,768,934	11,242,843	10,877,268	10,648,312	10,555,976	10,600,259	10,781,162	11,098,684
Lake States	Low	517,193	2,291,750	5,323,673	9,612,960	3,015,380	0	0	0	0	0	0	3,533,836
	Medium	5,120,637	11,027,127	17,719,470	25,197,665	21,317,482	14,236,717	10,290,200	7,949,257	9,392,784	13,977,215	19,269,805	25,270,552
	High	12,083,406	24,764,417	38,043,031	51,919,250	54,248,842	53,189,603	52,727,968	52,863,938	53,597,512	54,928,690	56,857,473	59,383,860
Northeast	Low	50,552	346,358	887,418	976,802	0	0	0	0	0	502,626	1,631,964	819,977
	Medium	751,825	1,656,934	2,715,326	3,230,072	2,104,172	1,322,587	1,050,968	1,433,852	2,276,353	3,266,246	4,185,548	3,075,091
	High	1,790,777	3,701,825	5,733,143	7,187,802	6,968,802	6,870,072	6,891,614	7,033,425	7,295,508	7,677,861	7,962,501	6,190,259
Northern Plains	Low	0	568,344	2,607,847	5,817,571	10,197,515	13,667,862	3,322,529	0	0	0	0	0
	Medium	4,599,361	9,930,110	15,992,247	22,785,772	30,310,685	36,487,167	28,409,137	21,062,494	14,447,239	12,242,079	11,579,232	13,407,381
	High	11,516,236	23,624,791	36,325,666	49,618,860	63,504,374	75,902,390	73,906,824	72,503,577	71,692,650	71,474,043	71,847,755	72,813,787
Southeast	Low	0	0	0	0	142,406	473,031	220,740	0	0	0	416,584	128,548
	Medium	56,020	174,987	356,901	601,762	909,569	1,280,323	1,030,393	700,864	751,342	1,094,027	1,223,347	554,749
	High	284,989	632,394	1,047,689	1,529,051	2,076,479	2,689,972	2,685,900	2,605,350	2,590,865	2,642,446	2,381,565	1,223,667
Southern Plains	Low	0	0	0	0	0	8,171	130,908	288,325	328,898	132,508	0	0
	Medium	35,112	91,898	170,358	270,492	392,301	535,784	700,941	887,772	944,756	751,772	580,462	439,143
	High	158,169	338,428	540,777	765,217	1,011,747	1,280,367	1,571,078	1,883,879	2,067,249	2,001,068	1,956,976	1,934,975
Other	Low	0	34,967	527,930	1,337,880	2,464,817	1,250,017	0	0	0	0	0	0
	Medium	922,216	2,042,549	3,360,998	4,877,564	6,592,247	5,846,324	4,215,036	2,781,865	2,347,647	2,491,108	3,379,917	4,996,882
	High	2,372,745	4,912,049	7,617,914	10,490,339	13,529,323	14,076,145	13,706,046	13,502,507	13,465,528	13,595,110	13,891,251	14,353,952
U.S. Total	Low	4,409,135	17,616,781	41,218,941	34,373,708	17,365,427	17,114,045	3,832,802	288,325	328,898	11,247,381	41,739,010	41,987,371
	Medium	37,347,706	81,026,732	131,037,077	146,804,426	123,052,263	102,606,140	80,426,338	85,783,285	102,911,786	132,925,747	165,371,352	166,127,172
	High	88,291,431	181,439,203	279,448,792	341,744,058	359,181,647	371,864,515	370,678,259	374,209,450	382,449,110	395,277,121	408,050,752	385,401,406

Figure 3. Possible information values in the Corn Belt

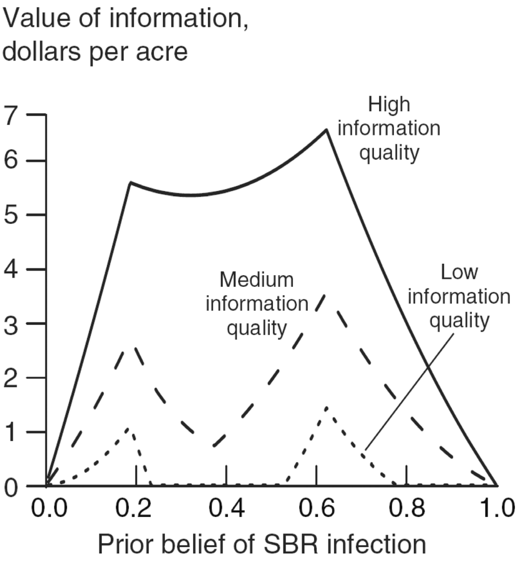


Table 5. Aggregate information values for the United States

Scenario	Information Quality: Low ($\alpha = 0.2$) (in Dollars)	Medium ($\alpha = 0.5$) (in Dollars)	High ($\alpha = 0.8$) (in Dollars)
Base case			
U.S. total	11,247,380	132,925,747	395,277,121
Average per acre	0.16	1.84	5.46
Risk aversion			
U.S. total	16,880,465	136,418,926	391,344,966
Average per acre	0.23	1.88	5.41
Price feedback			
U.S. total	28,773,280	130,259,030	376,391,350
Average per acre	0.40	1.80	5.20
Heterogeneous beliefs			
U.S. total	16,777,090	102,300,370	275,889,857
Average per acre	0.23	1.41	3.81

of low quality ($\alpha = 0.2$), there are some priors for which the information provided will not cause farmers to change their management behavior, thus producing no value at all.

Using estimated probabilities of infection for prior beliefs in each region and aggregating on a per-acre basis across all regions, we estimate in table 5 that the aggregate value of information ranges between \$11 million and \$395 million, depending on information quality. In the next section, we show how these information values were determined under the assumptions that farmers are strongly risk averse, that soybean prices are influenced by soybean-rust-induced yield losses, and farmers' prior beliefs are heterogeneous within each region. As can be seen in table 5, these scenarios all increase the lowest information values and reduce the highest values in comparison to the base case. Despite the broad range of information values estimated, all far exceed the program's estimated cost in the first year, which ranged between \$2.5 million and \$5.0 million (U.S. Department of Agriculture, 2005).[6] Because the value increases between \$2 million and \$3 million for each percentage point of uncertainty resolved by the framework, efforts to improve timeliness and accuracy of infection forecasts may well be cost-effective.

Alternative Scenarios

In the base case scenario described in the preceding section, we evaluate farmers' expected-profit-maximizing management decisions with and without information and estimate the value of information as the difference in expected profits between the two environments. In the following scenarios, the concept is similar but some assumptions are changed or relaxed in order to explore the sensitivity of the base-case estimates to these assumptions.

Alternative Scenario 1: Information Values of Risk-Averse Farmers

We first consider how our results change if farmers are strongly risk averse. More specifically, we assume farmers' preferences can be characterized by constant relative risk aversion (CRRA), with a coefficient of relative risk aversion equal to 4. This may be expressed with the utility function: $u(W) = -AW^{-3}/3$, where W indicates wealth, and A is an arbitrary constant. We made this assumption to throw into stark relief the effect of risk aversion on information values.

Using data from USDA's 2003 Agricultural Resource Management Survey, we estimate base wealth for each region by weighting farm households' net worth by their number of soybean acres. We find that wealth varies considerably across farm sizes and across the country, with the average soybean acre being associated with a household net worth of \$1,649,807 in Appalachia and \$1,348,667 in the Corn Belt, but only \$918,870 in Delta states. Average net worth is \$1,430,615 in Lake States, \$1,030,815 in the Northeast, \$1,389,427 in the Northern Plains, \$1,300,438 in the Southeast, and \$1,572,391 in the Southern Plains. Net worth for the average soybean acre of farms outside these regions is \$915,964. Calculating information values for risk-averse farmers' proceeds similarly to the base case described earlier, except that farmers are assumed to maximize expected *utility* rather than expected *profits*.

In only a few cases does the extreme level of risk aversion cause farmers' decisions to differ from the base case. This assumption changes information values, however, mainly because different information environments may lead to large differences in profit variability. For example, consider a farmer who would have applied the preventive strategy without information. Suppose that if armed with a high-quality forecast, the farmer chooses prevention in response to a "high-risk" signal and does nothing in response to "low risk." The information would cause her average profits to increase but would also cause her profit variability to increase, so the information would be valued less by this farmer than by another who is less risk-averse. When the information signal is of poorer quality, information may increase or decrease the amount of risk, so the information value may be relatively greater or smaller than in the risk-neutral base case.

Table 6 reports results from the analysis of risk-averse farmers. Differences from the base-case scenario are generally modest and vary somewhat across regions and information qualities. In the Corn Belt, for example, a strongly risk-averse farmer values low-quality information at \$0.37 per acre versus the base-case value of \$0.22. Alternatively, the same risk-averse farmer values high-quality information at \$5.96 per acre, which is slightly less than the value of \$6.01 in the base case. More realistic assumptions about the level of risk aversion would imply smaller differences from the base case.[7] U.S. aggregate information values (see table 5) range from almost \$17 million (low quality) to over \$391 million (high quality).

Alternative Scenario 2: Price Feedback Effects

The base case scenario assumed soybean prices were fixed at the May 2, 2005, futures price. However, both economic theory and historical evidence indicate that soybean prices vary with yield, and because each decision (prevent, monitor/cure, or no management) and each outcome (rust infection or no rust infection) leads to different yields, we consider the additional possibility that postharvest soybean prices are endogenous. Table 7 presents information values similar to those in table 3, except infestations and farm management decisions are assumed to influence market prices for soybeans.

Equilibrium soybean price is determined as follows: individual farmers, taking expected postharvest price as given, maximize their own profits, while the industry as a whole, which is made up of these individual profit-maximizing farmers, satisfies one of the equations below. In these equilibrium equations, the May 2 futures price equals the average of all potential end-of-season soybean prices, weighted by the market-perceived probabilities that these prices will be realized. In the case where no information is available, this means:

$$\begin{aligned}(6)\quad & \text{Prob}(\textit{RUST infection}) \times (\textit{Post-harvest price w/RUST infection}) \\ & + \text{Prob}(\textit{no infection}) \times (\textit{Post-harvest price w/o infection}) = \textit{Futures price.}\end{aligned}$$

With partial information, this condition becomes:

$$\begin{aligned}(7)\quad & \text{Prob}(\textit{infection and ``high risk'' signal}) \\ & \times (\textit{Post-harvest price w/infection and ``high risk'' signal}) \\ & + \text{Prob}(\textit{infection and ``low risk'' signal}) \\ & \times (\textit{Post-harvest price w/infection and ``low risk'' signal}) \\ & + \text{Prob}(\textit{no infection}) \times (\textit{Post-harvest price w/o infection}) = \textit{Futures price}.\end{aligned}$$

The above conditions are only correct if the geography of the soybean market coincides with that of the SBR infection and message probabilities. Given the wide variation in climate conditions across the United States and the global nature of

Table 6. Information values with risk aversion

Region	Prior Belief of Infection (Probability)	Base Wealth (Dollars)	No Info Decision (P, M, or N)	EU No Info.	CE of EU No Info. (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P, M, or N)	Low Risk Decision (P, M, or N)	CE of EU With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Appalachia	0.67	1,649,807	M	1.354	78,371	0.2	P	M	79,248	877	0.78
	0.67	1,649,807	M	1.354	78,371	0.5	P	M	81,249	2,878	2.57
	0.67	1,649,807	M	1.354	78,371	0.8	P	N	84,302	5,931	5.30
Corn Belt	0.55	1,348,667	M	0.889	93,500	0.2	P	M	93,772	272	0.37
	0.55	1,348,667	M	0.889	93,500	0.5	P	M	95,446	1,946	2.62
	0.55	1,348,667	M	0.889	93,500	0.8	P	N	97,925	4,425	5.96
Delta	0.55	918,870	M	(1.184)	96,556	0.2	M	M	96,556	0	0
	0.55	918,870	M	(1.184)	96,556	0.5	P	M	98,085	1,529	0.78
	0.55	918,870	M	(1.184)	96,556	0.8	P	N	104,795	8,239	4.21
Lake States	0.49	1,430,615	M	0.990	58,476	0.2	M	M	58,476	0	0
	0.49	1,430,615	M	0.990	58,476	0.5	P	M	59,251	775	1.45
	0.49	1,430,615	M	0.990	58,476	0.8	P	N	61,329	2,853	5.34
Northeast	0.62	1,030,815	M	(0.700)	42,017	0.2	P	M	42,241	223	0.47
	0.62	1,030,815	M	(0.700)	42,017	0.5	P	M	43,183	1,166	2.46
	0.62	1,030,815	M	(0.700)	42,017	0.8	P	N	44,635	2,618	5.53

Continued

Table 6. Continued

Region	Prior Belief of Infection (Probability)	Base Wealth (Dollars)	No Info Decision (P, M, or N)	EU No Info.	CE of EU No Info. (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P, M, or N)	Low Risk Decision (P, M, or N)	CE of EU With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Northern	0.43	1,389,427	M	0.929	70,461	0.2	M	M	70,461	0	0
Plains	0.43	1,389,427	M	0.929	70,461	0.5	P	N	71,022	562	0.64
	0.43	1,389,427	M	0.929	70,461	0.8	P	N	74,608	4,147	4.71
Southeast	0.76	1,300,438	M	0.493	2,375	0.2	M	M	2,375	0	0
	0.76	1,300,438	M	0.493	2,375	0.5	P	N	3,013	637	1.44
	0.76	1,300,438	M	0.493	2,375	0.8	P	N	3,910	1,535	3.47
Southern	0.51	1,572,391	M	1.181	24,516	0.2	M	N	24,543	27	0.02
Plains	0.51	1,572,391	M	1.181	24,516	0.5	M	N	26,295	1,778	1.17
	0.51	1,572,391	M	1.181	24,516	0.8	P	N	29,977	5,461	3.58
Other	0.53	915,964	M	(1.492)	68,666	0.2	M	M	68,666	0	0
	0.53	915,964	M	(1.492)	68,666	0.5	P	M	69,613	947	0.86
	0.53	915,964	M	(1.492)	68,666	0.8	P	N	73,620	4,954	4.52

Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. EU indicates "expected utility" and CE indicates "certainty equivalence," which is the certain level of profits with same utility as the actual, uncertain level of profits.

Table 7. Information values with price effects

Region	Prior Belief of Infection (Probability)	No Info Decision (P, M, or N)	EV No Info (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P, M, or N)	Low Risk Decision (P, M, or N)	Low Risk EV (Dollars)	EV With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Appalachia	0.67	M	78,519	0.2	P	M	84,533	79,442	923	0.83
	0.67	M	78,519	0.5	P	M	90,070	81,174	2,655	2.37
	0.67	M	78,519	0.8	P	N	100,507	84,540	6,021	5.39
Corn Belt	0.55	M	93,302	0.2	P	M	99,471	93,819	517	0.70
	0.55	M	93,302	0.5	P	M	101,722	95,424	2,121	2.86
	0.55	M	93,302	0.8	P	N	107,547	97,568	4,265	5.75
Delta	0.55	M	98,203	0.2	M	M	104,540	98,203	0	0
	0.55	M	98,203	0.5	P	N	112,914	99,763	1,560	0.80
	0.55	M	98,203	0.8	P	N	129,996	106,859	8,657	4.43
Lake States	0.49	M	58,608	0.2	M	M	59,945	58,608	0	0
	0.49	M	58,608	0.5	P	M	62,826	59,217	610	1.14
	0.49	M	58,608	0.8	P	N	67,108	61,239	2,632	4.93
Northeast	0.62	M	41,936	0.2	P	M	45,307	42,216	279	0.59
	0.62	M	41,936	0.5	P	M	47,192	43,152	1,216	2.57
	0.62	M	41,936	0.8	P	N	51,267	44,481	2,545	5.38

Continued

Table 7. Continued

Region	Prior Belief of Infection (Probability)	No Info Decision (P, M, or N)	EV No Info (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	High Risk Decision (P, M, or N)	Low Risk Decision (P, M, or N)	Low Risk EV (Dollars)	EV With Info (Dollars)	Value of Info Per Farm (Dollars)	Value of Info Per Acre (Dollars)
Northern Plains	0.43	M	70,621	0.2	M	M	72,032	70,621	0	0
	0.43	M	70,621	0.5	P	M/N	77,804	70,588	(33)	(0.04)
	0.43	M	70,621	0.8	P	N	83,612	74,551	3,930	4.47
Southeast	0.76	M	2,419	0.2	M	M	3,997	2,419	0	0
	0.76	M	2,419	0.5	P	N	7,570	3,037	618	1.39
	0.76	M	2,419	0.8	P	N	11,239	3,962	1,543	3.48
Southern Plains	0.51	M	24,807	0.2	M	M/N	30,006	24,703	(103)	(0.07)
	0.51	M	24,807	0.5	M	N	38,578	26,605	1,798	1.18
	0.51	M	24,807	0.8	P	N	48,787	30,456	5,649	3.71
Other	0.53	M	69,085	0.2	M	M	72,481	69,267	0	0
	0.53	M	69,085	0.5	P	N	78,162	70,097	830	0.76
	0.53	M	69,085	0.8	P	N	86,884	74,039	4,772	4.35

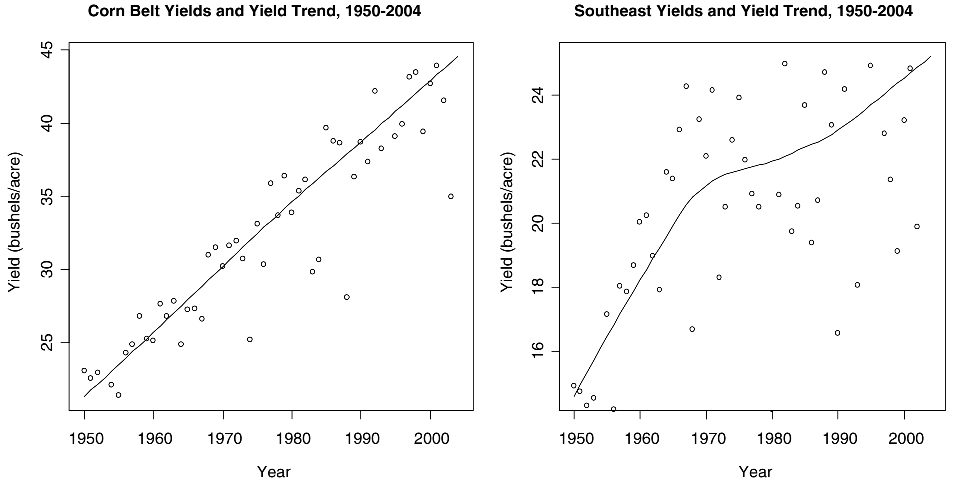
Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. In column headings, EV indicates expected value.

the soybean market, this is unrealistic. Allowing probabilities to vary by location, however, quickly renders the price equilibrium condition intractable. Even with the simplifying assumption that infection and message probabilities are homogeneous within each of the eight major soybean-producing regions,[8] the number of terms on the left-hand side of the partial information equilibrium equation climbs to 6,561. After all, there are three yield-determining outcomes ("high risk" message with infection, "low risk" message with infection, and no infection) possible in *each* region, producing 3^8 characterizations for the nation as a whole.

Though we do not explicitly model the regional interconnectedness that produces this host of outcomes, we allow for such effects by *not* including alternate location yield shocks as explanatory variables in our regressions of postharvest soybean price on regional yields (there are eight regressions—one for each region). Thus, our coefficient estimates will capture not only the effect of a specific region's yield on postharvest soybean price but also the effects of other yield shocks that are correlated with the region's own yield shocks (presumably those occurring in locations close in distance and weather). While these estimates provide some insight into how regional soybean prices and yields have been spatially correlated historically, there is no guarantee soybean rust will exhibit similar spatial effects as the weather and production shocks of the past decades. If, for example, soybean rust were to spread quickly over the entire soybean-producing part of North America, a rust-induced regional price increase would likely be greater than the increase resulting from yield loss caused by a more localized drought.

Our first step is to aggregate, using production-weighted averages, state-level data (U.S. Department of Agriculture 1950–2004) to the regional level. Next, in order to abstract from yearly variations in output while still accounting for productivity increases over time, we fit a smooth trend curve for yields in all nine soybean production regions. Examples of these trends for the Corn Belt and Southeast are given in figure 4.

Figure 4. Yield trends and shocks in the Corn Belt and Southeast



This fitting process allows us to calculate, for each region in each year, a percentage residual yield (i.e., the difference between actual yield and yield predicted by the trend, divided by the yield predicted by the trend). We approximate the percentage change in regional soybean prices by calculating the year-to-year difference in the natural logarithm of the real price. By regressing this value on the percentage residual yield, we obtain an estimate of the percentage change in price that would result from a percentage deviation from the yield trend.[9,10]

In computing the results in table 7, we first find the equilibria[11] in which all farmers within a region make identical management decisions. In just two cases, such equilibria do not exist: the Northern Plains with an information quality of 0.5 and the Southern Plains with an information quality of 0.2. For these regions, we consider equilibria where farmers apply one strategy to a share of acreage within a region and apply another strategy to the remainder. In these two cases, in equilibrium, farmers are indifferent between monitoring and no-management strategies when they receive the low-risk signal. An equilibrium results in the Northern Plains scenario when, in response to a low-risk signal, about 35% of acreage is monitored, the remainder is unmanaged, and the postharvest price, when the signal indicates low risk but infection occurs anyway, is $6.91. Similarly, the Southern Plains is in equilibrium when, in the face of low risk, about 27% of acreage is monitored; 73% is unmanaged; and the postharvest price, when the signal indicates a low risk-signal but infection occurs anyway, is $6.45.

For most regions, accounting for price effects has a small influence on information values. The effect is somewhat greater in the Corn Belt and Northern Plains

Figure 5. Density of farmers' heterogeneous prior beliefs in the Corn Belt

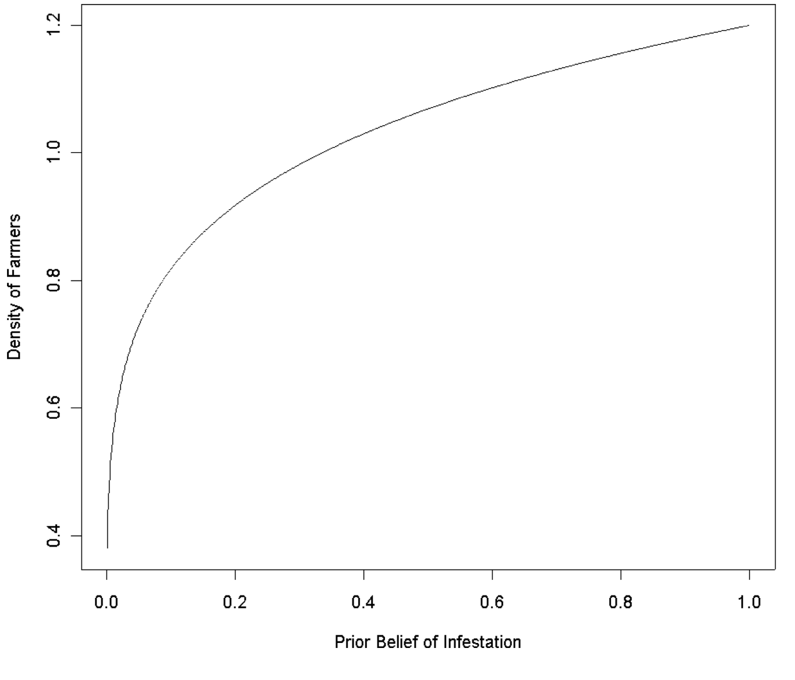


Table 8. Information values with heterogeneous prior beliefs

Region	Average Prior Belief of Infection (Probability)	"alpha" Parameter for Beta Prior	"beta" Parameter for Beta Prior	No Info Decision (P, M, or N)	EV No Info (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	Average Value of Info Per Farm (Dollars)	Average Value of Info Per Acre (Dollars)
Appalachia	0.67	2.00	1.00	M	78,644	0.2	239	0.21
	0.67	2.00	1.00	M	78,644	0.5	1,465	1.31
	0.67	2.00	1.00	M	78,644	0.8	3,957	3.54
Corn Belt	0.55	1.20	1.00	M	93,707	0.2	182	0.25
	0.55	1.20	1.00	M	93,707	0.5	1,132	1.53
	0.55	1.20	1.00	M	93,707	0.8	3,001	4.04
Delta	0.55	1.20	1.00	M	97,963	0.2	391	0.20
	0.55	1.20	1.00	M	97,963	0.5	2,360	1.21
	0.55	1.20	1.00	M	97,963	0.8	6,504	3.33
Lake States	0.49	0.95	1.00	M	58,573	0.2	137	0.26
	0.49	0.95	1.00	M	58,573	0.5	801	1.50
	0.49	0.95	1.00	M	58,573	0.8	2,185	4.09
Northeast	0.62	1.60	1.00	M	42,109	0.2	107	0.23
	0.62	1.60	1.00	M	42,109	0.5	660	1.39
	0.62	1.60	1.00	M	42,109	0.8	1,793	3.79

Continued

Table 8. Continued

Region	Average Prior Belief of Infection (Probability)	"alpha" Parameter for Beta Prior	"beta" Parameter for Beta Prior	No Info Decision (P, M, or N)	EV No Info (Dollars)	Information Quality (ϕ) (Scale 0 to 1)	Average Value of Info Per Farm (Dollars)	Average Value of Info Per Acre (Dollars)
Northern Plains	0.43	0.75	1.00	M	70,688	0.2	179	0.20
	0.43	0.75	1.00	M	70,688	0.5	1,077	1.22
	0.43	0.75	1.00	M	70,688	0.8	3,009	3.42
Southeast	0.76	3.20	1.00	M	2,408	0.2	81	0.18
	0.76	3.20	1.00	M	2,408	0.5	450	1.01
	0.76	3.20	1.00	M	2,408	0.8	1,111	2.51
Southern Plains	0.51	1.05	1.00	M	24,973	0.2	243	0.16
	0.51	1.05	1.00	M	24,973	0.5	1,465	0.96
	0.51	1.05	1.00	M	24,973	0.8	3,734	2.45
Other	0.53	1.13	1.00	M	69,159	0.2	234	0.21
	0.53	1.13	1.00	M	69,159	0.5	1,396	1.27
	0.53	1.13	1.00	M	69,159	0.8	3,846	3.51

Notes: In the decision column, M is monitor/cure. In other column headings, EV is expected value, and "alpha" and "beta" parameters are those in the beta probability distribution.

because yield shocks in these soybean-intensive regions have larger estimated price effects. In the Corn Belt, for example, the value of information increases from the table 3 amount of $0.22 per acre to $0.70 per acre when it is of low quality and declines from $6.01 to $5.75 when it is of high quality. In the Southeast, where the estimated price effects are far smaller, the values of both low- and high-quality information are unchanged at zero and $3.48 per acre, respectively.

When we account for price feedback effects, small changes in expected yield lead to small changes in expected price (i.e., the futures price). If information causes an increase in expected yield, expected prices tend to decline. If the expected price decline is large enough, farmers' total expected profits might decline because of the information, even though individual farmers find the information valuable (because individual farmers take prices as given). For soybean consumers, however, this price decline is a gain—it represents a transfer from producers to consumers. Of course, the opposite is true if the information causes a decline in expected yield: prices increase, and consumers experience a welfare loss because of the information's existence

Alternative Scenario 3: Average Information Values for Farms with Heterogeneous Beliefs

A third departure from the base case results comes from changing our assumptions about farmers' prior beliefs. Whereas in the base case we assume all farmers within a region hold the same prior beliefs about the probability of infection, in this scenario we assume farmers have heterogeneous prior beliefs. Specifically, we assume beliefs within a region are distributed according to a beta distribution with the beta parameter equal to one and the alpha parameter set so that the mean equals the prior probability of infection in the base case (table 3). This assumption implies that farmers' beliefs vary widely within each region.

The assumed distribution for the Corn Belt is plotted in figure 5. The height of the density curve shows the relative proportion of farmers assumed to have the prior belief plotted along the horizontal axis. We estimate average information values for each region and information quality by taking 1,000 random draws from the assumed beta distribution, using each draw as the value for P, calculating the associated information values from each draw, and then taking the average of the information values across all 1,000 draws (table 8).

In general, heterogeneous prior beliefs tend to reduce the highest information values and increase the lowest ones. The highest values decline because they are associated with the highest-value prior beliefs—those near the critical probabilities that mark the switching points between strategies. With heterogeneous beliefs, these high-value prior beliefs are averaged with lower value prior beliefs, bringing down the overall average. Conversely, the lowest value prior beliefs are averaged with higher value prior beliefs, which bring those information values up.

Conclusion

The value of disease information to farmers depends on many factors, but particularly their perceived risk of being infected with SBR at the beginning of the season and the accuracy of forecasts provided by the program. Over a broad range of plausible parameters, the value of information provided by the SBR Coordinated Framework could have been substantial even though the disease did not spread to the major soybean growing regions in the Midwest. If the forecasts were poor, resolving only 20% of SBR infection uncertainty for all fields planted with soybeans, the estimated value of the program was $11 million during the first year. If the forecasts resolved 80% of infestation uncertainty, the estimated value was $395 million. The estimated value is also sensitive to prior beliefs about the likelihood of infestation. Unlike forecast accuracy, however, the relationship between information value and prior beliefs is highly nonlinear. While some alternative prior beliefs would lead to lower information values as compared to our baseline, others give much higher values.

The sensitivity of information value to the extent of resolved uncertainty suggests that the potential value of information will be greatest for pest problems that can be forecasted accurately, that farmers have little experience with, and that have large potential impacts on crop production that can be mitigated using preventive management activities (Carlson). Other key drivers of the total value of information are the size and value of the crop in question. For instance, the near tripling of soybean commodity prices since 2005 would imply a near tripling of our estimated value of SBR forecasts, holding all else the same.

Two other more subtle features affect estimated information values: anticipated price shocks in the event of large SBR outbreaks and the risk aversion of soybean farmers. We find that both of these effects reduce the largest estimated values and increase the smallest ones, but the magnitudes of these effects are modest.

By examining the value of information across a range of forecast accuracies, we have illustrated the value of marginally improving information quality. Since the marginal information value appears large in the case of SBR, in future work it may be worthwhile to consider models that explicitly incorporate features of the information collection system. In the SBR framework, information quality is linked to the number of sentinel plots used for monitoring, where the plots are located spatially, and how frequently the sentinel plots are monitored. It would be interesting to consider the optimal mix of these policy choices. While such a model would be extremely complex, the potential social gains from its construction would seem to warrant the effort.

Such a model would need to capture the spatial and dynamic patterns of infestations. Our discrete two-period timing of information flows and decision making and the way we deal with spatial dependencies are crude relative to the continuous and spatially dependent processes that exist in reality. In a more sophisticated model, prior beliefs would be determined at different points in time for different farmers, since the timing of the growing season varies geographically. Even without the monitoring framework, many farmers would have had more information thantheir beginning-of-the-season prior beliefs, say from weather reports and news about infections further south. Thus, the relevant decision-time prior is itself uncertain at the beginning of the season. Because we found information to be valuable across many priors, integrating over these priors would likely lead to information values not drastically different from the ones we have estimated. A more sophisticated model, however, would provide insight into the appropriate structure of information systems—where and how frequently monitoring would be most valuable.

A more sophisticated model may also be able to account for the externalities associated with farmers' pest management choices. Each farmer's monitoring and fungicide application decisions affect the likelihood that his or her neighbors will be infected. This physical externality embodies another market failure that sits alongside the public information problem. While the optimal policy solution would likely involve separate tools for each problem, in practice, solving one problem may either mitigate or exacerbate the other.

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Endnotes

[1]In this case study, we do not consider farmers' planting decisions, only their fungicide application decisions, provided they do plant. By ignoring this decision, we underestimate the value of information provided by the framework.

[2]Costs and yield losses reported in table 1 are estimates. Yield data, before and after the arrival of *P. pachyrhizi* are not available for the United States, nor are efficacy trial data for U.S. fungicides. Efficacy data also were not available at the time of this study for climatic regions similar to the United States. Thus, to estimate treated and untreated yield impacts of soybean rust epidemics relative to rust-free yields, we evaluated impacts of rust on soybean yields in South America. Details are provided in an online supplement to Roberts et al.

[3]Poorly timed sprays could lead to the need for additional applications (Dorrance, Draper, and Hershman). We do not attempt to quantify the value of improved timing, which would likely increase the presented estimates for the value of information.

[4]The regions contain the following states: Appalachia (KY, NC, TN, VA, and WV), Corn Belt (IA, IL, IN, MO, and OH), Delta (AR, LA, and MS), Lake States (MI, MN, and WI), Northeast (CT, DE, MA, MD, ME, NH, NJ, NY, PN, RI, and VT), Northern Plains (KS, ND, NE, and SD), Southeast (AL, FL, GA, and SC), and the Southern Plains (OK and TX).

[5]From personal communication with Douglas G. Luster, Research Leader of USDA Agricultural Research Service, Foreign Disease Weed Science Research Unit.

[6]Totals depend on which fixed, start-up costs are included. Extension agents and land-grant professors volunteered their time, which is not counted in the cost estimate. The testing labs in Beltsville, Maryland, used equipment that had already been purchased, and USDA scientists involved in several other research projects carried out the tests.

[7]A farmer with this utility function and wealth of $200,000, values an additional dollar 16 times as much as a farmer with $400,000 and 625 times as much as a farmer with $1 million.

[8]Defined in "Prior Infection Probabilities" section.

[9]Only the 20 most recent observations (1984–2004) are included in this regression.

[10]Percentage change in price from year to year will depend not only on this year's yield shocks, but also on yield shocks that may have affected the previous year's price. However, including previous year yield residuals as an explanatory variable does not lead to significant changes in estimates of the coefficients on current-year price-shock effects.

[11]The relevant equilibrium condition is expressed by equation (7).

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